STEEL MAKING PROCESS SOLVING BY EXPERT SYSTEM

Gallová Š.[1]*, Gallo M.*[2]

[1] *Machine Tools Department, Faculty of Mechanical Engineering, Technical University of Košice*

[2] *Vyššie odborné štúdium pri SPŠ, Košice*

PROCES VÝROBY OCELE RIEŠENÝ PROSTREDNÍCTVOM EXPERTNÉHO SYSTÉMU

Gallová Š.[1]*, Gallo M.*[2]

[1] *Katedra výrobnej techniky, Strojnícka fakulta, Technická univerzita Košice*

[2] *Vyššie odborné štúdium pri SPŠ, Košice*

Abstrakt

Proces výroby ocele pozostáva z výroby surového železa, tavenej ocele v kyslíkovej peci, odlievania do blokov a pod. Použitie klasických metód riešenia problémov spojených s výrobou ocele naráža v súčasnosti na celý rad problémov, nedostatkov, obmedzení. Zavedenie expertného systému ako významnej aplikačnej oblasti umelej inteligencie prináša preklenutie mnohých problémov hlavne v súvislosti s narastajúcim množstvom pravidiel a obmedzení, ktoré sprevádzajú túto výrobu v procese jej riadenia. Zvlášť aktuálne sú požiadavky na odozvy v reálnom ease. Problémy sa vyskytujú na rôznych úrovniach a v rôznych krokoch procesu výroby ocele (kontinuálne odlievanie, žíhanie, valcovanie, rezanie a pod.), čo si vyžaduje koordináciu všetkých zainteresovaných zložiek, aby sa udržala optimálna produkcia.

Problém je definovaný určovaním aké zdroje priradiť ku každému produktu a aký proces a v ktorom čase tomu zodpovedá. Tieto priradenia musia spĺňať obmedzenia zariadenia, ktoré sú vo všeobecnosti v tvare pravidiel. Pravidlá sú odvodené z prevádzkových skúseností so zariadením a často sa menia v súvislostí so získavaním ďalších skúseností. Takto sa stáva tento problém problémom splnenia existujúcich ohraničení. Expertný systém je pravidlový. Pravidlá sú konštruované na základe teórie fuzzy množín, ktorá prináša novú kvalitu do procesov rozhodovania pri výrobe ocele. Umožňujú pracovať s neistými, nejednoznačnými, neúplnými, vágnymi informáciami o procese. Tieto informácie a znalosti majú hierarchickú povahu. Pôsobnosť znalostí pokrýva škálu od všeobecných a široko použiteľných znalostí ku špeciálnym, úzko použiteľným, od deskriptívnych znalostí k preskriptívnym. Platnosť znalostí sa pohybuje od istého k neistému. Samotné znalosti v danom expertnom systéme o riešenom probléme procesu výroby ocele sú jednak popisné (charakterizujú problémovú oblasť), jednak klasifikačné (rozhodujú o príslušnosti do tried). Osobitnú skupinu tvoria riadiace znalosti, na základe ktorých sa určuje kedy a ako aplikovať popisné a klasifikačné znalosti.

Lingvistické fuzzy pravidlá dokonalejšie korešpondujú s reálnym opisom skutočností, čo vedie k skvalitneniu rozhodovacieho procesu expertného systému.

Abstract

The steel manufacturing process consists of making pig iron from ore, producing molten steel in basic oxygen furnace, followed by casting into slabs, blooms or billets, [1,2]. The requirement for an expert system solution rather than a traditional methods in this environment arises when there is an extensive set of rules and restrictions, which govern how orders can be sequenced through the equipment being designed.

Applications of expert systems have been most popular in diagnostics and problem determination applications, where extensive human-machine dialogue is common. In the application of process control the demands of execution speed for real-time response and the requirement of dialogue with asynchronous events occurring in a process, creates significantly different environment and challenge for expert system tools currently available on process control computers.

Key words: steel making process, rule-based expert system, fuzzy rule, membership function

1. Introduction

The expert system is used for supervisory actions whereas lower level monitoring and control functions are performed by microprocessors and control computers. The application uses a rule-based expert system. The problem arises in various steps of the steel making process. This includes the basic oxygen furnace, ladle refining (in some plants) and continuous casting. The other steps of annealing, cold rolling, cutting etc. also require co-ordination to maintain optimum production, while servicing a variety of orders from customers.

The problem is defined as determination of what resources to allocate to each product and its accompanying process at what time. These allocations must satisfy the equipment constraints which are generally stated in the form of rules. The rules are derived from operation experience with the equipment and are often changing as more operational experience is gathered. Thus, the problem becomes a constraint-satisfaction problem.

2. PROBLEM SOLVING

A significant number of process industry manufacturing lines contain a critical resource or a type of equipment for which the sequence constraints are particularly restrictive. In this case an expert system approach can be used to develop a satisfactory production sequence for this resource. This system concentrates on the problem of allocating a single equipment resource to create multiple product variety continuously within the equipment constraints as dictated by the rules set up and learned from experience.

The production goals are transmitted to the area-level system at the steel plant, which has the responsibility of fulfilling the production goals for the mill, by month, by week and in general, meeting the orders for the customers. The area-level in this case also may maintain work-in-process inventory including the pool of off-spec products which could meet some of the orders with or without rework depending upon cost considerations.

There are two strategies, underlying all the others. These are:

forward reasoning (forward chaining)

backward reasoning (backward chaining).

In the forward reasoning all deductions are taken from the given data. A refinement can be achieved with a "breadth first" strategy in which in a given status of the inference component always all deductions are made, and a "depth first" strategy, in which all deductions building up on a inference step are processed first. If no solution is found with that, a so-called "back-training" is done, i.e. the inference process goes back to a preceeding configuration and tries to utilize a different possible conclusion as basis for the following deduction steps.

In backward reasoning all possibilities to a given goal are checked as to how the goal be deduced. If no possibility exists, subgoals are generated in order to deduce missing conditions. Here again, the refining breadth first or depth first strategies can be applied.

Inference here is a procedure, which selects and interprets rules. This is decisive for the efficiency of the system and works in three steps:

Determination of conflict set.

At first, it is determined, which rules are executable. In forward chaining these are all rules, whose condition part is met by data. In backward chaining only those rules are considered, whose action part helps to reach a predetermined goal (data). Thus a set of rules is given, the so-called "conflict set".

Conflict solution strategy.

In the second step a conflict solution strategy for the choice of a "firing rule" from the conflict set is applied.

Application of a rule.

In the last step the chosen rule is executed, i.e. the rule is applied to data, where depending on the chaining method the condition or the action part comes into effect.

The described strategy uses a combination of forward and backward chaining to achieve a reduction of complexity. The inference strategy of a problem solving component should ensure that in each situation the most promising a cost effective solution path is pursued.

In an intelligent control system, system behaviour can be described by a non-mathematical-knowledge base, such as a rule based, fuzzy logic or neural network model. A block-diagram of industrial control system with various levels is shown in Fig.1 - a strategy of described method for steel making process solving by expert system is generally created on this basis.

The task of "information processing" in a control system is to produce control actions on the basis of gathered system information. In a non-mathematical-knowledge based system, the information processing involves signal coding and decoding, associative memory and reasoning associated with mathematical algorithms under a numerical, multivalued (fuzzy) or symbolic framework. However, in mathematical model based control systems, the information processing is reduced to a "control law" or so-called "control algorithm" with numerical computation.

In a general sense, the function of "learning and adaptation" in a control system is to maintain the entire system (controlled system environment plus controller) performance at a satisfactory level even when the system environment is significantly perturbed. In order to make control system robust and adaptive, the system mathematical-model, control law, knowledge base or any other forms of control mechanisms should be automatically adapted to the changes of system environment through On-line identification, reasoning, knowledge acquisition and learning. In conventional programming we expect that all required information is provided before computation takes place. It makes no sense to try to balance a checkbook with missing numbers. In knowledge programming, this is not necessarily the case.

"Robustness" and "adaption" are considered as the most important properties for this industrial control system.

There were used (in created system) the linguistic fuzzy rules. The linguistic fuzzy rules are describing the qualitative relations between the major operating conditions. If the membership functions are defined as shown in fig.2, then the fuzzy rules can be represented as [3].

Fig.1 System model in industrial control

RULE (i,j) : "IF x_1 is H_{1i} and x_2 is H_{2i} ,

THEN y is O_{ij} "

where (i,j) $i = 0, \ldots, m$

$j = 0, \ldots, n$ denote rule numbers, and

H_{1i}, H_{2j} denote the linguistic values of x_1, x_2, which are represented by membership values M_{1i}, M_{2j}.

Similarly o_{ij} denotes the linguistic value of y with membership M_{yij}.

Fig.2 Membership function for x_1

The membership function of x1 can be described as follows:

otherwise

The membership function for $\mathbf{x_2}$, $\mathbf{M_{2j}}$ is the same.

The output **y** can thus be derived by the weighted average:

A self-learning algorithm was used in this designed system. The problem is to minimize the following "cost function" with the optimized values of (h_{1i}, h_{2j}, o_{ij}) based on the training data set $\{x_{1k}, x_{2k}, y_{kr}\}$:

Learning system can provide good performance while the "working environment" is close to the "learning environment". In practice, there is not always a good match between the working environment and the learning environment. As a result, the "generalization" becomes a critical measure to examine the learning performance. In a practical sense, the generalization means that an associative memory or system model formed by learning not only provides a good performance under the learning environment, but also provides a satisfactory performance even for a working environment never learned before. Obviously, if it lacks generalization, the resulting associative memory or model can not be applied in practice. The level of generalization mainly depends on the statistical distribution of the selected training patterns, the structure of the intelligent model and the learning approach used. The generalization commonly used in intelligent systems is related to the robustness or the adaptation popularly used in modern control techniques. How to design a learning system with good generalization is a key topic in any intelligent control system.

3. CONCLUSION

The fuzzy logic can encode expert (qualitative or linguistic) knowledge directly using fuzzy rules. However, the most difficult and time consuming task in developing a fuzzy system is to determine its membership function which minimize the error between the fuzzy model and the actual system outputs. The applications of neural networks can first extract the fuzzy rules through data clustering with unsupervised (or self-organized) learning. Then another neural network will be further used to construct a fuzzy associative memory (or so-called non-linear pattern mapping) with an optimized multidimensional membership function. As a result, the neural networks in a fuzzy system can serve as either a development tool or an adaptive component.

Functionally, a hierarchical computer system for industrial control can be generally divided into four levels, namely level one for dedicated dynamic control, level two for supervisory control, level three for coordination, production, scheduling and planning, and level four for information processing and management. With the integration of business management and production, a level five for information oriented global strategic decision making and management may be added. On the other hand, the computer integrated manufacturing system -CIM- was firstly proposed and investigated for discrete event dynamic (flexible manufacturing) system not long ago, and recently, the application of CIMS in process industry with continuous, batch and/or discrete event driven operations have also been explored.

A non-linear system modeling or control problem can be solved by either fuzzy or neural network technique indepedently. In general, a neural network can handle such kinds of task better, while the system under study is able to provide the I/O training patterns with rich information. However, on the other hand, if the system has rich linguistic knowledge, e.g. fuzzy rules, then a fuzzy system can be applied.

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